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A Coverage Dominance Approach for Sensor Deployment Optimization

Albert Hung Ren Ko, Anne-Laure Jousselme, Patrick Maupin
Decision Support Systems for Command and Control (DSS-C2) section
Defence R & D Canada - Valcartier
Quebec, Qc, Canada, G3J 1X5
Email: {albert.ko,anne-laure.jousselme,patrick.maupin}@drdc-rddc.gc.ca

***Abstract*—A Wireless Sensor Networks (WSN) usually consists of numerous wireless devices deployed in a region of interest, each able to collect and process environmental information and communicate with neighbouring devices. The problem of sensor deployment becomes non-trivial when we consider environmental factors, such as terrain elevation. We propose a Crowd-Out Dominance search (CODS) that makes use of topographic terrain information and inter-sensors relationship information to facilitate the search of the best sensor positions. The proposed method demonstrates better robustness to terrain complexity compared with traditional heuristic methods.**

Keywords:Sensor Deployment, Wireless Sensor Network, Optimization, Multi-Agent System.

I. Introduction

A Wireless Sensor Network (WSN) usually consists of numerous wireless devices deployed in a region of interest, each able to collect and process environmental information and communicate with neighbouring devices [5], [9], [13], [27], [28]. Hence, a WSN can be regarded as a Multi-Agent System [14], [16], [29] for territorial security, where individual agents cooperate with each other to avoid duplication of effort and to exploit other agent's capacities [1], [29]. Sensor deployment is an essential issue in WSN, as it affects how well a region is monitored by sensors. This is a critical issue as there are a number of high potential applications for sensor deployment, such as national defence [23], home security [30], industrial surveillance [11] and environmental monitoring. The primary goal for sensor deployment is generally two-fold: WSN should cover a region of interest as completely as possible, while minimizing the number of sensors deployed, and thus minimizing costs associated with sensor deployment.

Considering a region of interest monitored by sensors, one of the most critical concerns is the region coverage [9], [13], [18]–[20], [27], [28], [31]. In general, one of basic requirements for a WSN is that each location in a region of interest should be within the sensing range of at least one of the sensors. Another option is to have each location within a region of interest covered simultaneously by at least K sensors [28], [31]. Some deterministic methods have been proposed to address the problem of coverage. It has been shown that covering an area with disks of equal radius can be done in an optimal manner using a fixed deployment pattern [5], [13], [18], [27] or using Voronoi Diagrams to reduce sensor redundancy [10]. Similar results have been reported when multiple coverage of the target area is required [5], [19], [28], [31]. Besides, the majority of optimization methods proposed are deterministic [5], [13], and are generally functions of a fixed sensing range.

Most sensor deployment optimization methods published in literature assume that sensors are placed on a 2D plane, without taking into account the topographic terrain information [5], [10], [13], [18]. Nevertheless, the area of interest that requires sensor deployment is rarely completely flat, usually it contains buildings and some facilities. As a result, obstacles presented in environment, such vegetation, buildings, hills or valleys are somehow ignored in sensor deployment setting [5], [13].

However, the problem becomes non-trivial when we consider environmental factors. It would be somehow similar to an Art Gallery problem [8], [12], [15], [25], except that the number of obstacles depends on the position where a sensor is deployed. Given N sensors to be deployed in an area with M possible positions, the possible combination number of deployment will be $\frac{M\cdot(M-1)\cdot(M-2)\cdots(1)}{(M-N)\cdot(M-N-1)\cdots(1)}$. In general, M is rather large, and this makes exhaustive search unfeasible. For example, given an area of $100m \times 100m$, even if we place a grid of $1m$ and restrict sensors to be deployed only on the corner of a grid, there will be $10,000$ possible sensor positions. The problem has been pointed out in [3], [21], and with such a high dimensionality it cannot be solved directly, especially if the terrain exhibits some irregularities.

To our knowledge, there are no ideal solutions for this NP-hard problem yet. Heuristic search methods such as random search may be applied, in the hope that a suitable local optimum will emerge during the search. Some more systematic search algorithms such as genetic algorithms or simulated annealing may also be implemented [3], [6], [26], in the hope that they would perform better

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14. ABSTRACT
A Wireless Sensor Networks (WSN) usually consists of numerous wireless devices deployed in a region of interest, each able to collect and process environmental information and communicate with neighbouring devices. The problem of sensor deployment becomes non-trivial when we consider environmental factors, such as terrain elevation. We propose a Crowd-Out Dominance search (CODS) that makes use of topographic terrain information and inter-sensors relationship information to facilitate the search of the best sensor positions. The proposed method demonstrates better robustness to terrain complexity compared with traditional heuristic methods.

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than random search.

Facing this challenge, we follow a new avenue. Our aim is to achieve automated sensor deployment optimization based on realistic topographic terrain information, and realistic sensor modelling. However, we face instantly two problems: 1) terrain effects on sensors; 2) interference among sensors. The former causes the unevenness of coverage among most positions, i.e., some positions can cover a larger area than others because of terrain advantage. Given that each position now will have different coverage, we need to test each position in order to know the best place to deploy a sensor, as traditional optimal sensor deployment schemes become inadequate. The latter causes the problem of redundant coverage by multiple sensors. Because more sensors mean higher cost for sensor deployment, it does not make much sense if two sensors cover the exact area, or if they demonstrate some large redundancy. This also raises the issue of relativity among sensors: A sensor that can cover the most pixels among its peers may turn to be useless, because all pixels it covers are also covered by other sensors. As a consequence, if we desire to reduce redundancy in sensor coverage, we thus need to test combinational effect of all sensors deployed in all possible positions.

Hence, there are a few questions that need to be answered:

1) Given an initial sensor deployment pattern on a region, if a search algorithm moves one sensor at a time, how to decide which sensor to move?
2) Given an initial sensor deployment pattern on a region, if a search algorithm moves one sensor at a time, how to decide where to move to?
3) Given that exhaustive search is not feasible, what may be the best way to deal with such as a complex problem? Random search? Genetic approaches? Or simulated annealing?
4) What is the influence of terrain irregularities on the performance of search algorithms?

Many search algorithms do not consider these questions, and the randomness is rampant during the search process, with only a few exceptions. We propose a Crowd-Out Dominance search (CODS) that makes use of terrain information and inter-sensors relationship information to facilitate the search. Moreover, our method selects explicitly which sensor to move at each search step, as well as which positions this sensor may move to. In order to validate our proposed method, we also compare our results with a number of heuristic methods, including random search, genetic algorithms, and simulated annealing.

II. Problem Statement

Although there are some common notions on critical issues such as coverage [2], [7], [19], [31], there are few comprehensive frameworks that have been proposed for sensor deployment optimization. In most cases, sensor deployment optimization is regarded as an overly complex problem, thus generic heuristic algorithms are often used for the optimization task [6], [26]. As a result, we believe that some important concepts worth to discuss on that are still not clearly defined or outline.

One of the most important problems addressed in the literature is the sensor coverage problem. The coverage concept is a direct measure of quality of service of WSN [22].

Given a sensor $\mathbf{s_i}$ with a sensing range d_r and a point of interest $\mathbf{p_j}$ with a distance d_{ij} away from sensor $\mathbf{s_i}$, we first define the visibility $v(\mathbf{s_i}, \mathbf{p_j}) = 1$ if the point $\mathbf{p_j}$ is visible to sensor $\mathbf{s_i}$, and $v(\mathbf{s_i}, \mathbf{p_j}) = 0$ otherwise. Once the visibility is defined, the coverage of the sensor $\mathbf{s_i}$ to the point $\mathbf{p_j}$ can be calculated:

Definition 1 (Single Sensor Binary Coverage): The sensor binary coverage $c(\mathbf{s_i}, \mathbf{p_j})$ of a sensor $\mathbf{s_i}$ with detection range d_r on the point $\mathbf{p_j}$ can be defined as:

$$c(\mathbf{s_i}, \mathbf{p_j}) = 1, \text{if } \max(0, d_r - d_{ps}) \cdot v(\mathbf{s_i}, \mathbf{p_j}) > 0 \quad (1)$$

$$c(\mathbf{s_i}, \mathbf{p_j}) = 0, \text{otherwise} \quad (2)$$

If there are N sensors deployed, instead of just one single sensor, then the coverage of a point $\mathbf{p_j}$ can be defined as:

Definition 2 (WSN Binary Coverage): The WSN binary coverage $c(\mathbf{p_j})$ on a point $\mathbf{p_j}$ can be defined as:

$$c(\mathbf{p_j}) = 1, \text{if } \sum_{i=1}^{N} c(\mathbf{s_i}, \mathbf{p_j}) > 0 \quad (3)$$

$$c(\mathbf{p_j}) = 0, \text{otherwise} \quad (4)$$

where $\mathbf{s_i}$ denotes a sensor among total N sensors, $1 \leq i \leq N$. Again, a probabilistic coverage on a point can be implemented if the sensor behavior is known:

With the knowledge of the coverage between sensor $\mathbf{s_i}$ and all points of interest, the overall coverage by sensor $\mathbf{s_i}$ can be defined by aggregation. If there are m points of interest, then the coverage by a sensor $\mathbf{s_i}$ can be defined as:

Definition 3 (Coverage by a Sensor): The coverage $c(\mathbf{s_i})$ by a sensor $\mathbf{s_i}$ can be defined as:

$$c(\mathbf{s_i}) = \sum_{j=1}^{m} c(\mathbf{s_i}, \mathbf{p_j}), 1 \leq j \leq m \quad (5)$$

where $\mathbf{p_j}$ is a point, $1 \leq j \leq m$, in a region of interest R. This definition applies for both binary and probabilistic coverages.

Given N sensors to be deployed on a terrain, and m points in a region of interest, the global coverage $c(S)$ can be defined as the sum of coverage of all points of interest, which in turns is a function of all sensors deployed, $\{\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_N\}$:

Definition 4 (Global Coverage):

$$c(S) = \sum_{j=1}^{m} c(\mathbf{p_j}), \forall j, p_j \in R \tag{6}$$

where $\mathbf{p_j}$ is a point, $1 \leq j \leq m$, in a region of interest R. Again, the same definition works for both binary and probabilistic coverage settings.

Apparently, the global coverage $c(S)$ is a function of terrain elevations $p_{j,z}$, $1 \leq j \leq m$ of all points of interest in region R, sensor positions $s_{i,x}, s_{i,y}$ and sensor elevations $s_{i,z}$, $1 \leq i \leq N$. For simplicity, we denote the series of $p_{j,z}$ as $\mathbf{p_{j,z}}$ and the sensor positions and elevations as $\mathbf{s_{i,x}}, \mathbf{s_{i,y}}, \mathbf{s_{i,z}}$, respectively:

$$c(S) = \Phi(\mathbf{p_{j,z}}, \mathbf{s_{i,x}}, \mathbf{s_{i,y}}, \mathbf{s_{i,z}}) \tag{7}$$

Thus, the goal for sensor deployment is to position sensors in a way that global coverage is maximized:

$$\{\mathbf{s_{i,x}}, \mathbf{s_{i,y}}\} = \arg\max c(S) \tag{8}$$

$$= \arg\max \Phi(\mathbf{p_{j,z}}, \mathbf{s_{i,x}}, \mathbf{s_{i,y}}, \mathbf{s_{i,z}}) \tag{9}$$

Note that $\mathbf{p_{j,z}}$ and $\mathbf{s_{i,z}}$ are terrain effects and the system has no controls on these factors.

Here we notice that we derive global coverage $c(S)$ not by sensors, but by points in a region interest. The reason is that it is far less costly to take into account multiple coverage effects by points of interest rather than by sensors. We simply cannot know the extent to which a sensor has duplicated coverage with other sensors unless we examine all points of interest that may potentially be covered. This causes some problems in optimization, because we cannot simply add up coverage from all sensors to obtain global coverage. Thus, we cannot split the problem into independent individual optimization problems, because optimization of individual sensor coverage would not be equal to the overall global coverage. Moreover, because the sum of coverage of all sensors does not equal to global coverage, we cannot evaluate the fitness of an individual sensor only based on its coverage achieved.

Consequently, it may be not trivial to evaluate the performance of each sensor, despite that we know the global performance of WSN. The problem is subtle but critical. This is the main reason why a systematic search for global coverage optimization is unavailable, and people would turn to more heuristic search methods such as random search, simulated annealing or genetic algorithms.

That being said, heuristic search methods have their own problems as well. Even with restricted operation choices, the search space is still large if terrain exhibits little regularity. As we stated in the introduction, given N sensors to be deployed in an area with M possible positions, the possible combination of deployment will be $\frac{M\cdot(M-1)\cdot(M-2)\cdots 1}{(M-N)\cdot(M-N-1)\cdots 1}$. In general, $M \gg N$, and the number of possible combinations may become colossal. As a consequence, heuristic search methods may not perform well if no further information is provided to guide the search.

For such a problem, environmental complexity such as terrain irregularities may make it unfeasible to procure a global optimum solution, but the implementation of adequate algorithms may reduce search space, accelerate search process, or improve the quality of local optima found.

III. Proposed Method

The goal of current problem is to maximize the coverage of the sensor network deployed, instead of coverage of any individual sensors. Recall that we consider the sensor network as a Multi-Agent System, each agent should act for the best benefit of the group, and not for itself. Hence, each agent should not look for the maximum payoff (coverage by a sensor) for itself, but rather look for the maximum payoff of the group (WSN). To do so, actions taken by an agent must also consider effects on other agents and actions that other agents may take.

Given the high dynamic nature of the problem, it is quite costly to predict the behaviors of other agents and the consequences of these behaviors in such a complex and dynamic setting. Hence, the perfect information concerning all other agents is simply not available. Given the multitude of actions and the number of agents, the great majority of payoffs of combination of actions for each player are simply unknown at the time of decision making. In other words, it is impossible to figure out an action with strict domination for any agent.

In the context of sensor deployment, this means that we can only evaluate global performance, but we do not know the exact action each sensor should make. Hence, we argue there are two fundamental issues for such a high complexity problem: a) how to evaluate individual sensors; b) how sensors should be moved. We thus propose Crowd-Out Dominance Search (CODS) in an attempt to attenuate the problem. Under CODS, the former means to choose the sensor using an adequate fitness function, and the latter means to take possible actions that may increase the gain of the overall WSN. This forms an iteration of sensor selection and sensor deployment, with adequate fitness function for sensor selection and adequate information for sensor deployment.

In order to understand the concept of CODS better, we introduce some important issues at the section below.

A. Which Sensor to Move - Sensor Evaluation

As we stated before, the sum of coverage by all sensors does not equal to global coverage. Hence, we cannot simply evaluate the performance of each sensor by its coverage in the hope that global coverage would be optimized. Thus, if we desire to have more systematic approaches than random methods, first we should find a way to evaluate individual sensors.

1) Marginal Contribution in Coverage as Fitness Function: Given a sensor network $S \backslash \mathbf{s_i}$ without a sensor $\mathbf{s_i}$, the effect of adding the $\mathbf{s_i}$ to S is the marginal contribution of $\mathbf{s_i}$.

However, if more than one sensor are moved at the same time, then the increase of marginal contribution of any individual sensors cannot guarantee an increase in global coverage. This is due to the fact that marginal contribution works by calculating the additional marginal benefits that a sensor brings to a network, given that all other sensors remain at the same places. If more than one sensor are moved at the same time, the condition under which we derive marginal contribution is simply not the same.

Another way to see this is through the fact that global coverage is composed of points with unique coverage and points with multiple coverage. Thus, if we move more than one sensor, the number of points with unique coverage may increase, but the number of points with multiple coverage may decrease. We can ensure that the number of points with multiple coverage stays the same only when we move one sensor at a time.

Hence, the marginal contribution has two important properties:

1) Marginal contribution can serve as a fitness function to evaluate sensors.
2) Marginal contribution can serve as a fitness function only if we move one sensor at a time.

2) Implement Marginal Contribution under Binary Coverage: In sensor network, this marginal contribution for $\mathbf{s_i}$ would be :

$$\varsigma(\mathbf{s_i}) = c(S) - c(S \backslash \mathbf{s_i}) \tag{10}$$

However, under binary coverage setting the unique coverage of sensor $\mathbf{s_i}$ would be exactly the marginal contribution of sensor $\mathbf{s_i}$. The unique coverage of sensor $\mathbf{s_i}$ is defined as the number of points that only $\mathbf{s_i}$ covers under binary coverage definition. The advantage of using unique coverage is that it can be easily calculated at the same time as we calculate global coverage, and thus that we do not need to do additional calculation of $c(S \backslash \mathbf{s_i})$ in order to obtain $\varsigma(\mathbf{s_i})$.

In the context of sensor deployment, we shall pay attention to two things: its coverage and its redundant coverage. Redundant coverage is important because it indicates duplicated efforts made by different sensors, and thus represents exactly such interference. We notice that in a complex environment duplicated effort may be made by more than two agents. In the context of sensor deployment, this happens when more than one sensor cover the same point of interest. We define such a phenomenon as multiple coverage. If there are N sensors deployed, instead of just one single sensor, then the coverage of a point $\mathbf{p_j}$ can be defined as:

Definition 5 (Multiple Coverage on a Point): The multiple coverage $\varphi(\mathbf{p_j})$ on a point $\mathbf{p_j}$ can be defined as:

$$\varphi(\mathbf{p_j}) = \sum_{i=1}^{N} c(\mathbf{s_i}, \mathbf{p_j}) \tag{11}$$

where $\mathbf{s_i}$ denotes a sensor among total N sensors, $1 \leq i \leq N$. This definition applies for both binary and probabilistic coverage settings.

Since we already have knowledge on multiple coverage measure for each point in a region of interest, we can derive unique coverage of each sensor deployed under binary coverage setting. If there are m points of interest, then the unique coverage by a sensor $\mathbf{s_i}$ can be defined as:

Definition 6 (Unique Coverage by a Sensor): The unique coverage $\varsigma(\mathbf{s_i})$ by a sensor $\mathbf{s_i}$ can be defined as:

$$\varsigma(\mathbf{s_i}) = \sum_{j=1}^{m} \max(c(\mathbf{s_i}, \mathbf{p_j}) - \max(\varphi(\mathbf{p_j}) - 1, 0), 0) \tag{12}$$

where $\mathbf{p_j}$ is a point, $1 \leq j \leq m$, in a region of interest R.

Alternatively we can define a set of points that uniquely covered by a sensor $\mathbf{s_i}$:

Definition 7 (Set of Points with Unique Coverage): If a point $\mathbf{p_j}$ is covered only by by a sensor $\mathbf{s_i}$, i.e., $\forall \mathbf{p_j}, c(\mathbf{s_i}, \mathbf{p_j}) = 1, \varphi(\mathbf{p_j}) = 1, 1 \leq j \leq m$, then we denote it as:

$$\mathbf{p_j} \triangleright \mathbf{s_i} \tag{13}$$

Then the unique coverage $\varsigma(\mathbf{s_i})$ by a sensor $\mathbf{s_i}$ is simply a number of points $\{\mathbf{p_j} \triangleright \mathbf{s_i}\}$:

$$\varsigma(\mathbf{s_i}) = \sum_{j=1}^{n} \mathbf{p_j} \triangleright \mathbf{s_i}, 1 \leq j \leq n \tag{14}$$

The unique coverage $\varsigma(\mathbf{s_i})$ is the marginal contribution in coverage under binary coverage settings, and it satisfies both comparability and monotonicity, thus it does reflect the effect that a sensor brings to a network. Thus, unique coverage $\varsigma(\mathbf{s_i})$ is the fitness function that we evaluate individual sensors with binary coverage. That being said,

we also notice that the sum of unique coverage would be smaller than global coverage in case that multiple coverage exists:

$$\sum_{i=1}^{N} \varsigma(\mathbf{s_i}) < c(S),\ if\ \exists j, \varphi(\mathbf{p_j}) > 1 \tag{15}$$

Hence, the marginal contribution does not converge to global coverage. The unique coverage of each sensor is important because it represents marginal contribution of each sensor to the WSN under binary coverage definition. Thus, the fitness function for each sensor should be exactly this unique coverage. Furthermore, given that only one sensor can be moved at a time, the fitness function can inform the system which sensor to move.

Under binary coverage, CODS implements unique coverage to select the sensor that is required to be moved. That is, among all sensors deployed, the one with the least unique coverage would be crowded out, and thus should be moved in the next iteration.

3) Sensor Selection: Once marginal contribution of each sensor is calculated, the one with the least marginal contribution would be selected as the sensor to move at the next iteration:

Definition 8 (Crowded-Out Sensor): The crowded-out sensor $\tilde{s}$ can be defined as:

$$\tilde{s} = \arg \min_{i=1 \cdots N} \varsigma(\mathbf{s_i}) \tag{16}$$

We believe that the problem should be tackled in a way that only a sensor is allowed to move at a time with marginal contribution as fitness function. Because simultaneous displacements of sensors may change the multiple coverage patterns among sensors greatly, it becomes impossible to capture inter-sensors relationship and to make a systematic deployment.

B. Where to Deploy Sensors - Position Selection

1) Environmental Information: To better guide the search process, CODS takes advantages of terrain information and inter-sensors information to facilitate the search. In order to accomplish this, CODS makes use of more properties than just global coverage for optimization. This is true especially when some partial information with focus on environment may be procured.

Thus, in order to indicate potentially better positions for a moved sensor to move in and to reduce the number of such positions, we define the dominance of each position. If there are m points of interest, then the dominance of a certain point $\mathbf{p_i}$ can be defined as:

Definition 9 (Static Dominance of a Position): The static dominance $\tilde{d}(\mathbf{p_i})$ of a certain point $\mathbf{p_i}$ can be defined as:

$$\tilde{d}(\mathbf{p_i}) = \sum_{j=1}^{m} c(\mathbf{p_i}, \mathbf{p_j}), 1 \leq j \leq m \tag{17}$$

where $\mathbf{p_j}$ is a point, $1 \leq j \leq m$, in a region of interest R, and $c(\mathbf{p_i}, \mathbf{p_j})$ is the same as sensor coverage $c(\mathbf{s_i}, \mathbf{p_j})$, except that sensor $\mathbf{s_i}$ is viewed as a position.

The dominance of a position $\tilde{d}(\mathbf{p_i})$ defined in the previous section is based on the static environment, i.e., we calculate the dominance of each position without considering the presence of sensors. The advantage of the use of static environmental information is that the calculation only needs to be done once, and thus it does not need additional cost during the course of search. The disadvantage is that since environmental information is static, it does not guarantee the true dominance with the presence of other sensors. The use of static environmental information provided a better guided search than purely random search, but still there is an element of randomness in search.

By contrast, the dynamic environmental information calculates the exact dominance with all interference of other sensors and terrain elevations. To calculate the exact dominance, first we can define a set of points that remain uncovered by any sensors:

Definition 10 (Set of Uncovered Points): If a point $\mathbf{p_j}$ is uncovered by any sensors, i.e., if it satisfies the condition $\forall \mathbf{p_j}, c(\mathbf{p_j}) = 0, 1 \leq j \leq m$, then we denote any uncovered points as:

$$\mathbf{p_j} \triangleright \emptyset \tag{18}$$

, where $\emptyset$ denotes the empty set. Then dynamic dominance of a position can be derived.

Definition 11 (Dynamic Dominance of a Position): The dynamic dominance $\check{d}(\mathbf{p_i})$ of a certain point $\mathbf{p_i}$ can be defined as:

$$\check{d}(\mathbf{p_i}) = \sum_{j=1}^{n} c(\mathbf{p_i}, \mathbf{p_j}), \mathbf{p_j} \in \{\{\mathbf{p_j} \triangleright \emptyset\} \cup \{\mathbf{p_j} \triangleright \mathbf{s_i}\}\} \tag{19}$$

where $1 \leq j \leq n$. We only calculate points that are either uncovered or only covered by selected sensor $\tilde{s}$, because only these points are relevant when we move only sensor $\tilde{s}$. Given dynamic dominance $\check{d}(\mathbf{p_i})$ on all posible positions, the position with the largest dynamic dominance can be easily defined:

Definition 12 (Largest Dynamic Dominance Position): A point $\check{p}_i$ with largest dynamic dominance can be defined as:

$$\check{p}_i = \arg \max \check{d}(\mathbf{p_i}) > \theta \tag{20}$$

This position would thus be the target position of $\tilde{s}$.

IV. EXPERIMENTS

In order to verify the validity of the proposed method, to understand crowd-out effect, static and dynamic dominance effects, we carried out a number of experiments on terrains with different irregularities. Note that we are simply unable to test all terrain types for two reasons: a) there are infinite types of terrain, and even categorization may not be feasible; b) currently we simply do not have enough realistic terrain data that provide large variations in terrain irregularities. Hence, we work another way around, first we define a standard deviation of terrain elevation as irregularity, and then we generate artificial terrains using different standard deviation and test different search algorithms.

A. Experimental Protocol

We deploy 8 sensors in an area with size $100m \times 100m$, thus the problem has the complexity of $10000 \times 9999 \times \cdots \times 9993$ combinations, which is almost 10^{32}. The coverage is based on binary setting, and each sensor is supposed to have a radius of $30m$ of detection range. Sensors are deployed one meter high above the ground, so there is an asymmetry between detecting positions and detected positions. Terrain has various elevation variations, the elevation variations are in Gaussian distribution with standard deviation from 0 m to 1.2 m and a mean of 0. Terrain is completely flat with only 0 m of standard deviation, but can be quite complex with 1.2 m of standard deviation.

Note that we expect the terrain to be fairly random, since there may be a number of obstructions in the real world, such as buildings and vegetations. The smoothness of terrain is a variable that differs in different environments, it is thus of interest to test algorithms under various terrain types. Moreover, although in some cases the terrain variation seems to be large, the effect is largely attenuated by the fact that sensors are deployed one meter high above the ground, and not on the ground.

To introduce asymmetry in the experiment, sensors would be placed one meter above the ground instead of on the ground. We tested several methods, including traditional deterministic pattern [5], [13], Random Search, Simulated Annealing, Genetic Algorithm, and CODS methods. In CODS with crowd-out effect, we select sensor for displacement using marginal contribution, but do not use terrain dominance information. In CODS with dynamic dominance, we implement dynamic dominance information, such that selected sensor would know exactly which position to move to maximize the global coverage.

Each method makes 500 displacement iterations in a test, with 30 tests in total, except for traditional deterministic pattern, genetic algorithm and CODS with dynamic dominance. Traditional deterministic pattern makes only one deployment, whereas CODS with dynamic dominance makes far fewer iterations, but with various number of displacement evaluation in each iteration. In all tests except for traditional deterministic pattern, the initial sensor positions are set up in a random way. Note that 500 displacement evaluations are set so that all heuristic methods have similar time cost as in CODS with dynamic dominance.

For genetic algorithm, we set up a population of 10 individuals, hence there would be 10 displacement evaluations in each generation. Thus, genetic algorithm only contains $\frac{500}{10} = 50$ generations to be comparable with other methods. Crossover rate is 0.9 and uniform crossover operator is implemented. Mutation rate is 0.05, and the disturbance in case of a mutation is a Gaussian distribution with standard deviation $\sigma_r = 10$m. For simulated annealing, we set $\alpha = \frac{1}{3}$ and $\beta = \frac{1}{2}$ for temperature function, and $\sigma_r = 10$m for displacement distance, the same as in genetic algorithm.

B. Experimental Results

Table I shows experimental results. Traditional deterministic deployment pattern has the lowest coverage among all methods tested. This is not surprising given that traditional deterministic deployment does not consider terrain elevations.

Among purely heuristic methods, we notice that simulated annealing with displacement of only one sensor at a time generally performs better than random search.

Genetic algorithm apparently performs better than simulated annealing. Also, genetic algorithm has the best performance when the terrain irregularity is low. Although genetic algorithm may displace one sensor at a time as well as all sensors at the same time, we notice that after a few iterations there is a striking similarity among individuals in the population. Usually fit individuals differentiate from one another only with one or two different genes. The implication is that genetic search is closer to displace one sensor at a time after a few iterations.

Although genetic algorithm does well in flat terrains, CODS schemes perform better than purely heuristic ones as terrain becomes more and more complex. The crowd-out mechanism has a clear effect on global coverage, but the effect becomes stronger when the irregularities grow larger. The dynamic dominance scheme can be promising in improving performance of crowd-out scheme, especially when terrain irregularities are large.

To summarize, CODS methods perform generally better than heuristic ones in complex terrains. CODS with dynamic dominance performs well when terrain irregularity is large, whereas CODS with only crowd-out mechanism has better performances when terrain irregularity is small.

Table I: Coverage percentage on the target areas for sensor deployment. 8 sensors in total are deployed in an area with size $100m \times 100m$, each sensor has a radius of $30m$ of detection range, and all sensors are placed one meter above the ground. The coverage is based on binary setting. Terrain elevation variations are in Gaussian distribution with standard deviations from 0 m to 1.2 m. Sensors are deployed one meter high above the ground. Each method makes 500 iterations in each test with 30 tests in total, except for traditional deterministic deployment, Genetic Algorithm and CODS with Dynamic Dominance. The mean and the standard deviation of these 30 tests are shown. std denotes for standard deviation. Best performances are shown in bold.

Method / Terrain Elevation	Random Search t	Simulated Annealing One at a Time	Genetic Algorithm
0.0 m	98.88(0.44)%	99.66(0.25)%	99.99(0.04)%
0.1 m	74.37(0.92)%	75.62(1.15)%	**79.77(0.71)**%
0.2 m	58.03(1.31)%	59.91(1.25)%	**65.05(1.04)**%
0.3 m	49.99(1.13)%	51.26(1.35)%	57.91(1.08)%
0.4 m	44.73(1.34)%	46.63(1.09)%	53.11(1.72)%
0.5 m	39.94(1.15)%	42.60(1.65)%	49.53(1.44)%
0.6 m	37.29(1.22)%	40.29(1.58)%	46.27(1.77)%
0.7 m	34.99(1.22)%	37.46(1.93)%	45.06(1.76)%
0.8 m	33.45(1.47)%	35.27(1.78)%	43.77(1.53)%
0.9 m	32.41(1.60)%	34.86(2.13)%	42.39(1.55)%
1.0 m	31.27(1.69)%	32.84(1.91)%	40.49(1.85)%
1.1 m	30.48(1.78)%	32.11(2.05)%	39.80(1.97)%
1.2 m	29.13(1.00)%	31.72(2.25)%	40.23(2.03)%
Method / Terrain Elevation	**Fixed Pattern [5], [13]**	**CODS Crowd Out Effect**	**CODS Dynamic Dominance Effect**
0.0 m	**100.00**%	99.51(0.55)%	99.51(0.55)%
0.1 m	70.26%	77.76(1.12)%	76.64(1.30)%
0.2 m	53.11%	64.19(1.55)%	62.96(1.38)%
0.3 m	40.74%	**58.59(1.37)**%	58.41(1.96)%
0.4 m	32.97%	**54.82(1.49)**%	54.58(1.28)%
0.5 m	23.51%	51.35(1.40)%	**52.87(1.66)**%
0.6 m	25.07%	49.27(1.25)%	**54.90(1.08)**%
0.7 m	13.96%	48.00(1.63)%	**51.14(2.50)**%
0.8 m	22.97%	46.53(1.63)%	**54.48(0.97)**%
0.9 m	20.44%	45.79(1.92)%	**52.34(1.41)**%
1.0 m	9.11%	44.16(1.26)%	**53.77(0.32)**%
1.1 m	12.74%	44.07(1.33)%	**52.28(0.74)**%
1.2 m	24.07%	43.93(1.36)%	**51.88(1.27)**%

V. Discussion

Experimental results on our sensor deployment framework suggest that the CODS is fully feasible and shows good promise in optimizing sensor deployment. CODS performs generally better than random search and simulated annealing.

A. Terrain Dominance Analysis

Although all terrains are generated with Gaussian distribution with elevation mean equal to 0 and various

Table II: The properties of static dominance distribution.

Measurement / Terrain Elevation	Mean	Standard Deviation	Skewness	Kurtosis
0.0 m	2143.5	555.2	-0.3190	1.9272
0.1 m	1369.5	339.6	-0.3857	2.0931
0.2 m	975.9	262.6	-0.1224	2.1556
0.3 m	763.2	252.5	-0.0288	2.4841
0.4 m	618.2	264.1	0.0096	2.4584
0.5 m	499.6	260.2	0.1801	2.4178
0.6 m	426.1	259.8	0.3585	2.3606
0.7 m	373.1	251.8	0.5088	2.5073
0.8 m	330.2	243.8	0.6750	2.7266
0.9 m	304.4	236.7	0.7379	2.7836
1.0 m	278.3	230.8	0.8713	3.0141
1.1 m	260.6	223.1	0.9578	3.2250
1.2 m	245.7	218.0	1.0067	3.3596

elevation standard deviation, their dominance exhibits a quite different pattern. Reminding that dominance is defined as the number of points that a sensor position can cover, dominance distribution would to be a uniform distribution when terrain is completely flat, but would shift from negatively skewed to positively skewed as terrain elevation standard deviation increases, as Table II. As terrain becomes more complex, average dominance decreases sharply, as well as standard deviation of dominance, but the former decreases in a larger rate the latter. On the other hand, both skewness and kurtosis increase. Note that even complete terrain does not exhibit a uniform dominance, this is because positions situated at borders of terrain cover far fewer points that those in the centre.

To summarize, our experimental results indicate that:

1) Given that exhaustive search is not feasible, simulated annealing seems to slightly outperform random search in sensor deployment. Genetic algorithm outperforms both random search and simulated annealing.
2) Marginal contribution, e.g., unique coverage, makes use of inter-sensors information to facilitate search in sensor deployment optimization.
3) Our experimental results on CODS crowd-out mechanism suggest that sensor with the minimum marginal contribution should be displaced.
4) Dynamic dominance takes into account terrain information to facilitate search in sensor deployment optimization, it can thus be explored to decide where a sensor should be deployed.
5) Terrain irregularities deteriorate the performance of all search algorithms, but CODS with dynamic dominance performs considerably better than other algorithms tested in case of large irregularity.

Furthermore, our experimental results encourage the use of both terrain information and inter-sensor infor-

mation. Terrain information can be transformed into both static and dynamic dominances, whereas inter-sensor information can be summarized using marginal contribution. Thus, we suggest that the sensor with the least marginal contribution should be displaced. To our knowledge, no similar initiatives concerning aspects listed above have ever been reported in the literature.

Our future work will be to measure and to characterize natural terrain irregularities using dominance distribution, and to select the best suitable search algorithm for sensor deployment.

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